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Review

Uncertainty-Aware Planning of EV Charging Infrastructure and Renewable Integration in Distribution Networks: A Review

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Abstract

Transitioning from internal combustion engines to electric vehicles (EVs) is critical for fighting climate change. This requires widespread adoption of Electric Vehicle Charging Stations (EVCSs). Integrating EVCSs and renewable energy sources (RESs) into distribution networks (DNs) is vital for a sustainable transportation system while enhancing power generation in an environmentally friendly manner. This review explores challenges and opportunities of EVCS and RES integration, concentrating on EV charging-demand uncertainty modeling, forecasting algorithms, planning techniques, and the impacts on DN. It discusses forecasting algorithms in terms of learning-based and non-learning-based methods. EVCS planning algorithms are also discussed, involving deterministic and stochastic methods. The technical, environmental, reliability, and economic impacts of EVCS-RES on DNs are discussed. It explores optimization strategies to minimize these impacts, incorporating them as objective functions. Additionally, the survey examines the methods of incorporating EVs and RES in DN, optimizing EVCS allocation while addressing EVCS impacts on voltage regulation, power loss, and network reliability. The importance of energy management systems and advanced forecasting techniques in balancing power fluctuation and improving efficiency is emphasized. Finally, it identifies open problems and future directions for forecasting and optimizing EVCS-RES integration in the networks. These findings are highly relevant for designing resilient and efficient modern power systems that leverage RES and EVCS in the grids.

Keywords: distribution networks; electric vehicles; electric vehicles charging station; uncertainty; optimization techniques; renewable energy sources

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Academic Editor: Michael Negnevitsky

Received: 22 January 2026
Revised: 16 February 2026
Accepted: 21 February 2026
Published: 24 February 2026

1. Introduction

The reliance on fossil fuels for conventional transportation and power grids is driving global warming and depleting reserves [1], requiring a shift to alternative energy sources [2]. The transportation sector accounts for 25% of global CO_2 emissions and 55% of oil consumption [1,3], with an expected demand growth of 54% by 2035 [4].

With the growing environmental concerns, Electric Vehicle Charging Station (EVCS) integration offers a promising solution to reduce CO_2 emissions and other environmental issues (air pollution and global warming) [5,6]. Electric vehicles provide environmental and economic benefits over traditional gasoline or Internal Combustion Engine (ICE) vehicles [7]. Advances in battery technology and increasing awareness of clean energy have enhanced EV production and sales [8]. In 2021, EV sales doubled to 6.6 million units,

 https://doi.org/10.3390/en19051131

bringing the global total to approximately 16.5 million, which is three times the number in 2018 [9]. However, the growth in EVCS development due to increased EV adoption presents challenges to the grid, including increased peak load demand, shortened transformer lifespan, harmonic distortion, and hampering the system's overall performance [10,11]. Extensive EV adoption can also worsen grid issues such as peak-to-valley load variance, transformer capacity, and risk of system failure [11]. These lead to voltage drops, power imbalances harmonic distortions, and influence power quality [12]. EV introduces complex issues like uncertainties, dynamic loading conditions, and proper charging control strategy requirements [13].

Some earlier studies [7,8] used EVs to design networks while minimizing system loss and optimizing the voltage profile. However, the planning model did not take renewable energy sources like PhotoVoltaic (PV) into account. This review manuscript provides a comprehensive survey of the combined integration of EVCS andRenewable Energy Sources (RESs) into modern power grids. It explores advanced techniques aimed at enhancing grid stability, energy efficiency, and system resilience. Some recent work has addressed optimal siting and sizing of EVCS, considering load profiles and grid constraints, while other work has emphasized renewable energy integration through distributed generation. Incorporating RESs in the grid is vital for sustainable electricity generation to meet the growing demand [7]. Though RESs and EVs offer environmental benefits to the Distribution Network (DN), their variability and unpredictability challenge grid stability and reliability [7,14]. Conversely, RESs can provide clean energy for EVs and other loads in the power system, especially in fossil fuel-dominated regions [2,15].

In the context of EVCS-RES integration, uncertainty relates to variability in renewable generation (for example, solar irradiation and wind speed), EV charging-demand patterns, and load variations. It can be represented with probabilistic forecasting, scenario generation, stochastic programming, or resilient optimization. Planning precision, investment effectiveness, and operational viability are all enhanced by including uncertainty. Planning outcomes may not be reliable under real operational conditions if uncertainty modeling is ignored.

The capacity of a planning system to sustain satisfactory performance in unpredictable operational situations is referred to as robustness. Usually, scenario-based sensitivity analysis, variance of objective functions, or worst-case performance are used to assess it. Robust planning avoids financial losses, unforeseen stability problems, and infrastructure reconfiguration. It improves long-term operational stability.

Reliability reflects the system's ability to continuously supply electricity without interruption and is commonly evaluated using indices such as System Average Interruption Frequency Index (SAIFI), System Average Interruption Duration Index (SAIDI), or Expected Energy Not Supplied (EENS). Concentration of load is increased with high EV penetration. Supply variations are introduced by RES intermittency. Service disruptions, feeder overloading, and voltage instability might result from this EVCS-RES integration in the existing distribution network. Planning with reliability lowers the risk of outages, enhances service quality, and keeps the grid resilient when EV penetration is high. Power supply continuity may be jeopardized if reliability is neglected.

Sustainability encompasses environmental and long-term operational considerations, including CO_2 emission reduction, renewable penetration level, and life-cycle cost minimization. Long-term economic viability, environmental compliance, and compatibility with decarbonization objectives are all guaranteed by sustainable planning.

This paper uniquely provides a detailed review of EVCS and RES integration in the power grid, aiming to enhance system performance through robust application and ensuring efficient control. It analyzes various techniques for uncertainty modeling and forecasting EV charging demand, using both learning-based and non-learning-based methods. The primary goal is to provide valuable insights for policymakers and stakeholders, energy planners, and researchers in designing resilient and efficient power systems, leveraging the potential of RESs and EVCSs.

This review covers EVCS planning algorithms, considering technical, economic, reliability, and environmental influences on DNs. Additionally, the survey looks at the integration of EVs and RESs in DNs, considering various optimization strategies used for allocating them in the grid. This paper also assesses the impacts of EVCS and RES integration in the grid, highlighting challenges related to voltage regulation, power quality, and network reliability. This work further emphasizes the importance of forecasting models for managing power imbalances and enhancing operational efficiency.

Key outcomes from the survey and future research direction are outlined to address these challenges, emphasizing the need for continued innovation and collaboration among stakeholders.

1.1. Related Work

Technological advancements in power systems are essential for reducing CO_2 emissions and addressing environmental issues. Integrating RES and EVs into the grid is critical for neutralizing CO_2 emissions and cost-effective electricity generation, transmission, and distribution. However, this integration makes the system more complex, needing strategic planning for smooth network operation Distribution Generation (DG) [15]. EVCS and RES incorporation in the DN significantly influences its performance. In [16], the authors highlighted the power quality challenges that RESs and EVs pose to DN operations. The authors concluded that integrating RESs and EVs into a smart grid requires standards, regulations, and advanced technologies such as smart metering, Artificial Intelligence (AI), and smart Energy Storage Systems (ESSs).

Other studies, such as [17,18], have reviewed optimization models applied to the optimal allocation of EVCSs and RESs in the DN. The authors in [17] surveyed various approaches for optimally placing EVCSs from the perspective of Distribution Network Operators (DNOs), Charging Station Operators (CSOs), EV owners, and environmental factors, along with their respective objective functions and security constraints. The study evaluates charging procedures, control, management, and EV flow coordination within EVCSs and DNs, discussing alternative optimization strategies and their impacts on the DN, environment, and economy. Similarly, the authors in [18] surveyed and categorized recent optimal DG allocation studies addressing DG integration problems, analyzing the features of optimization methods, objective functions, their performances; summarizing significant findings; and giving some advantages and disadvantages. They finalized their paper by highlighting the Optimal Distribution Generation Algorithm's critical role in RES integration and reducing carbon emissions, providing insights and perspectives for researchers on recent Optimal Distribution Generation Algorithm methods. In conclusion, they emphasized that previous studies suggest the technical feasibility of clean fuel technologies, but their economic viability remains uncertain; however, diversifying the mobility sector with clean electricity, hydrogen, and carbon-neutral fuels could better address climate change and carbon emissions.

Additionally, in [19], the authors reviewed EV charging control, enhancing charging station infrastructural design. The study covers EV types, global standards, and converter architectures. They investigated the role of EVCSs in the penetration of RESs in the DN. The authors suggested the use of semiconductor devices and noise filters to improve the control of the inverter's power. In addition, new techniques to improve power quality and grid stability were recommended for application in the DN amid the widespread adoption of EVCSs in the DN.

The abovementioned works from the literature concentrate on specific aspects like the impacts of RESs and EVCSs on DNs and the optimal allocation of RESs and EVCSs in DNs. From an all-inclusive perspective, most of the previous work has mainly focused on the integration of EVCSs and RESs while considering uncertainty modeling of EVCSs, EV forecasting algorithms, EVCS planning, and algorithms. It has also examined the impacts and benefits of RESs and EVCSs on the grid, along with RES integration in DNs in terms of technical and economic criteria, such as power losses, voltage stability, and cost optimization. However, the previous work did not give sufficient attention to environmental impacts and long-term reliability assessments, leaving these critical aspects underexplored in comparison.

Many existing review articles [20,21] on the planning and integration of RESs and EVCSs are largely concerned with system planning and integration methodologies. Although they include traditional forecasting techniques, they do not focus on advanced forecasting techniques for uncertainty modeling. Most previous studies [8,21] do not sufficiently examine or include advanced forecasting approaches into their evaluations of planning and integration frameworks. As a result, they fail to explain how AI-based forecasting approaches might improve planning precision and efficacy, especially in uncertain settings like changing renewable generation and different EV consumption patterns.

The purpose of this review is to investigate and analyze the prospects for, problems with, and future directions of combining RESs with EVCSs in DNs. This includes examining current research; identifying open problems; and giving useful insights to policymakers, researchers, and industry stakeholders. This review also looks into the technical, environmental, reliability, and economic implications of EVCS-RES integration.

Table 1 highlights that although previous surveys addressed EVCS planning and RES integration, they lacked comprehensive coverage of AI-based forecasting, uncertainty analysis, and multi-objective synthesis. The current review uniquely integrates traditional and AI forecasting methods, recent optimization techniques, and practical challenges within a unified and comprehensive framework, demonstrating its broader scope and updated contribution.

Table 1. Comparison of current review with existing surveys.

Features	Ref. [8]	Ref. [17]	Ref. [18]	Ref. [19]	Ref. [20]	Ref. [21]	Current Review
EVCS planning	✓	✓	✓	✓	✓	✓	✓
RES integration	✓	✓	✓	✓	✓	✓	✓
Traditional forecasting	✓	✗	✗	✗	✓	✓	✓
AI-based forecasting	✗	✗	✗	✗	✗	✗	✓
Uncertainty propagation analysis	✗	✗	✗	✗	✓	✓	✓
Multi-objective synthesis	Limited	Limited	Limited	Limited	Limited	Limited	Comprehensive
Recent optimization algorithms	✓	✓	✓	✗	✗	✓	✓
Challenges, policies, and incentives	✓	✓	✓	✗	✗	✗	✓

Unlike previous surveys, which focused on optimization approaches and system planning methodologies, this evaluation presents an integrated analytical framework that integrates forecasting accuracy, uncertainty propagation, and multi-objective planning performance. By combining forecasting methods (statistical, machine learning, and deep learning) with EVCS-RES allocation models, this study offers a structured examination of how predictive uncertainty affects voltage stability, system losses, economic cost, and reliability indices. This posture allows for a stronger difference from previous surveys and identifies forecasting-driven planning as a primary research focus rather than a secondary issue.

Recent breakthroughs in intelligent energy management for AC microgrids have shown that bio-inspired and adaptive control algorithms may effectively coordinate RESs and battery energy storage systems (BESSs) under stochastic operating circumstances. In [22], bio-inspired optimization techniques are used to coordinate BESS dispatch in AC microgrids, resulting in statistically validated reductions in operational costs, network losses, and emissions under variable renewable generation and demand profiles. Coordinated active–reactive power dispatch through BESS offers dynamic voltage support and congestion control, which are critical for handling large-scale EV charging in distribution networks with significant renewable penetration. As a result, adopting BESS-based uncertainty reduction measures into EVCS planning frameworks can greatly increase system resilience and operational reliability.

By systematically assessing and incorporating forecasting methodologies into planning and integration, it addresses a fundamental gap and provides routes to improve system reliability and performance. The rest of this paper is organized as follows: Section 2 discusses the incorporation of EVCSs into the DN, considering uncertainty modeling, and various planning algorithms, highlighting the technical, economic, and environmental impacts of EVCSs on the distribution network. Section 3 presents an in-depth review of EV and RES integration into the DN. Section 4 presents the discussion and conclusions of the work. Finally, this survey gives a thorough knowledge of EVCS-RES integration and proposes strategies for building resilient and sustainable power networks.

1.2. Research Questions

- How can forecasting methodologies be systematically incorporated into EVCS and RES planning to improve system reliability, optimization, and resilience under uncertainty?
- What are the key technical, economic, and environmental challenges in integrating EVCSs and RESs into distribution networks, and how can robust system optimization strategies effectively address them?
- In what ways can innovative planning algorithms enhance the long-term sustainability, reliability cost-effectiveness, and operational efficiency of EVCS–RES-integrated distribution systems?

2. Electric Vehicle Charging Stations (EVCSs)

The power sector is becoming more attractive due to several factors: (i) the rapid growth of charging infrastructures, (ii) environmental initiatives, (iii) a vast reduction in fossil fuel usage, and (iv) the adoption of smart strategies. In addition, with the increase in the availability of fast-charging stations, EVs can receive a charge as swiftly as traditional ICE vehicles are refueled.

The main inputs for EVCS planning models are predicted EV demand. Decisions about feeder loading, voltage magnitude profiles, load flow calculations, and investment sizing are all directly impacted by forecast errors. While inflated forecasts might result in large infrastructure and unnecessary expenditure, underestimated EV demand could cause localized voltage dips and inadequate charging capacity. Consequently, forecasting accuracy has a major impact on the optimal siting and sizing results. Forecast uncertainty penetrates through the objective functions and restrictions in planning frameworks. Calculations of power loss, voltage deviation indices, and system loading levels are all affected by changes in the anticipated demand for EV charging. These forecasting variations affect the Pareto-optimal solutions and can change the optimal bus locations for EVCS units when stochastic or scenario-based optimization is used.

This section explores the different charging uncertainties, methods involved in optimization algorithms, and many other topics.

2.1. EVCS Uncertainty Modeling

Here, the different approaches used in modeling uncertainties associated with various input parameters in a grid integrated with EVs are explored. The key interest is to tackle EV load-forecasting activities. Factors like users' behavior, mileage, battery capacity, travel time, arrival/departure time, charging time, the customer arrival pattern, overall charging demand, etc., contribute hugely to the uncertainties in EV charging demand. Figure 1 categorizes the various uncertainties into three input parameters within the grid. These inputs can be utilized to model Electric Vehicle (EV) load.

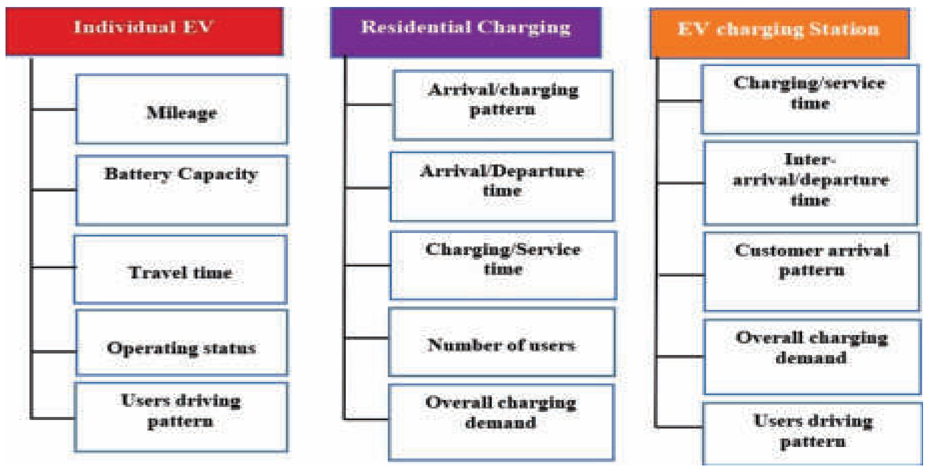

Figure 1. Parameters used for uncertainty modeling of electric vehicle demand.

Arrival time, departure time, starting State Of Charge (SOC), and charging duration are the uncertainty characteristics that were chosen for EV demand modeling because they have a fundamental impact on the peak coincidence and temporal aggregation of charging loads in distribution networks. According to empirical mobility research, the main source of EV load uncertainty is variation in user behavior and battery parameters. Realistic depictions of charging concurrently, load variety, and peak demand variations are made possible by stochastically modeling these characteristics. Thus, the chosen probabilistic/scenario-based framework preserves computational feasibility for planning-level optimization studies while capturing the fundamental causes of EV demand uncertainty. In recent years, numerous research papers have addressed uncertainty modeling problems by applying the techniques listed in Figure 2. These methods cover advanced techniques to enhance predictive accuracy and efficiency [23]. As summarized in Figure 2, these techniques are broadly classified into two categories: learning-based and non-learning-based. Each of these categories is further divided into several subcategories, as discussed below.

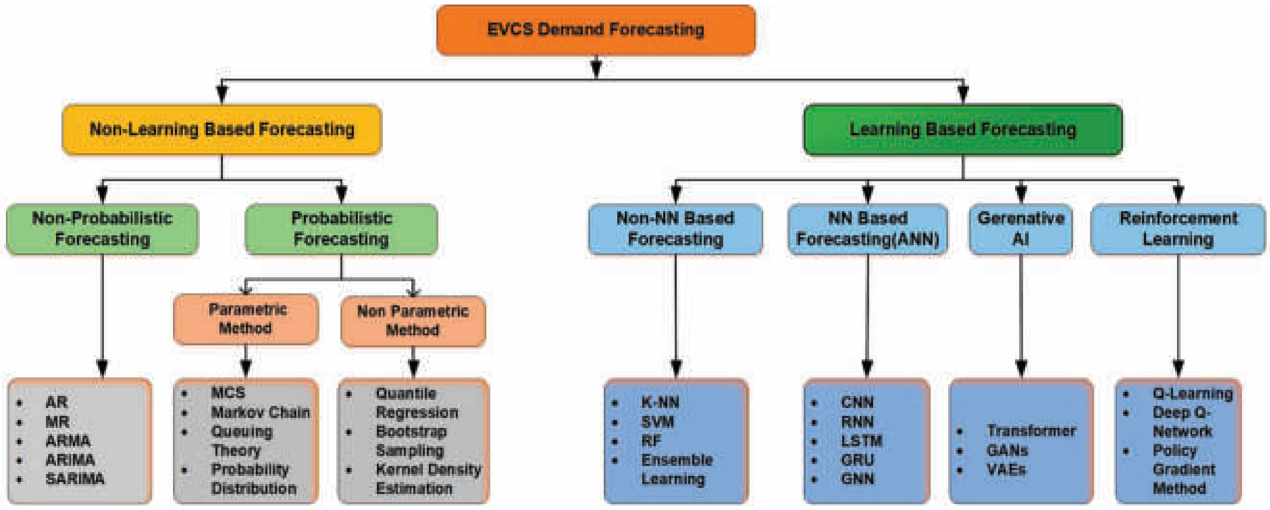

Figure 2. A summary of EV charging demand-forecasting methods.

2.1.1. Non-Learning-Based EV Charging Demand-Forecasting Methods

A brief overview of non-learning-based EV charging demand-forecasting methods and applications is discussed in this section.

Non-Probabilistic Forecasting Method

This section examines various autoregressive techniques used as non-probabilistic methods for forecasting EV charging demand. Non-probabilistic forecasting of EV charging demand frequently employs various auto-regressive techniques [1], like Auto-Regression, Moving Average, Auto-Regressive Moving Average (ARMA), Auto-Regression Integrated Moving Average (ARIMA), and Seasonal Auto-Regression Integrated Moving Average (SARIMA). Among these, ARIMA is the most used method for the application of EV load forecasting [1]. For instance, in [2] the authors use the traditional ARIMA to forecast EV charging demand based on past data. Similarly, the authors in [3] apply the ARIMA time-series algorithm to predict daily EV charging demand using historical data. In [4], a comparison of three time-series models, SARIMA, ARMA, and ARIMA, revealed that SARIMA outperformed the other two techniques. It achieved the lowest score on three evaluation criteria: root mean square error, mean absolute error, and mean absolute percentage error.

Probabilistic Forecasting Method

This method offers a lot more value to the forecasting process of EV charging demand by accounting for uncertainty in the prediction. Probabilistic methods are divided into two: parametric and non-parametric approaches [1]. Forecasting EV charging demand is a complex challenge due to limited publicly available data and the unpredictable, stochastic nature of EV charging behavior [5]. In tackling these pressing challenges, researchers employ probabilistic methods, such as Monte Carlo Simulation (MCS) [6] and Markov Chain [7] for EV demand forecasting. The advantage of this algorithm is that, in the absence of actual EV charging-demand data, probabilistic methods can effectively simulate EV charging demand by considering its stochastic nature. These methods primarily rely on generating random samples to approximate the system's behavior. However, the forecasting accuracy can drastically decrease if the random samples significantly deviate from the actual system characteristics [1].

- Parametric Probabilistic methods

Parametric probabilistic techniques include MCS [6], Markov Chain [7], etc. These categories of the probabilistic approach predict future results by assuming that the data follows a specified system defined by a set of parameters. These techniques estimate the parameters from historical data to depend on historical data, accounting for uncertainty in future forecasts [1].

1. Monte Carlo Simulation (MCS)

This technique assesses the impact of risk and uncertainty in the prediction model. EV charging-demand forecasting under the MCS approach is enhanced by a thorough analysis of the achievable results [1]. MCS methods are computational techniques that rely on repeated random sampling to obtain numerical results [10]. In [9], MCS was introduced as a forecasting model to forecast charging loads during weekdays and weekends. This technique has proven to have outstanding performance for EV load forecasting among the many frequently used probabilistic methods [10,11]. In [11], the authors developed the probability density functions (PDFs) for the different charging factors, like state of charge (SOC), travel mileage, and charging duration. In [12], PDFs are used to calculate regional EV charging demands employing the MCS method. Computing the EV load-forecasting model using MCS is intensive and requires considerable time, especially for complex scenarios involving multiple variables and uncertainties [1].

Using MCS for EV charging-demand forecasting can be time-consuming due to the need to generate a large number of random samples, especially for complicated scenarios with various variables and uncertainties. Furthermore, the efficiency of MCS can be significantly diminished by notable departures from the actual system features, as its success is highly dependent on the accuracy of its random samples.

2. Markov Chain (MC)

The MC forecasting technique works with a series of random values, where the succeeding value depends on the present one. This means they are not entirely random [1]. Several papers [12,13] propose dynamic EV charging-demand forecasts and models that simulate the unpredictable driving, traffic, and charging behaviors of EVs using the Markov Chain technique. The authors in [13] introduce an innovative EV demand-forecasting model that leverages MC theory to incorporate the inherent randomness of user behavior, traffic patterns, and weather conditions. Similarly, the authors in [7] introduce the space–time-forecasting model considering the road network complexity, temperature, and user behavior. They use the Markov dynamic decision model to determine the best (optimal) route for selection. In [14], the taxi trip rules are simulated using trip order data and the origin–destination analysis method. The optimal path is selected through the Markov dynamic decision model. Additionally, the charging decision model considers the influence of user psychology, specifically to analyze the anchoring effect.

The assumption of constant transition probabilities underlies the usage of Markov Chain for EV charging-demand forecasting, which might not be sufficient to capture the dynamic nature of EV charging behaviors. Because the model finds it difficult to adjust to changing patterns and trends in EV consumption, this constraint may result in predicting accuracy that is lower.

- Non-Parametric Methods

Non-parametric forecasting methods are flexible and data-driven, and they are used to model and predict EV charging demand without relying on predefined data distribution or equation [1]. Alternatively, modeling and demand predictions are made by observing the data patterns and trends, effectively handling complex, nonlinear relationships [1].

Many non-parametric methods, like quantile regression (QR) [24], kernel density estimation (KDE) [25–27], and diffusion-based KDE (DKDE) [27], are used for EV charging-demand prediction. The authors in [24] proposed a method to improve the prediction of the energy demand of every EV, incorporating many mobility features of EV users, using quantile regression models to generate probabilistic forecasts of the energy demand for the next-day energy consumption and parking time.

2.1.2. Learning-Based EV Charging Load-Forecasting Methods

There are a few methods for learning-based forecasting methodologies. These include machine learning (ML), reinforcement learning (RL), and generative AI [28]. From Figure 2 above, ML is divided into two categories: non-NN-based models and NN-based models. The learning process of NN-based models depends on artificial neural networks (ANNs), while non-NN-based models operate oppositely.

Non-NN-Based Machine-Learning Forecasting

Forecasting models such as Random Forests (RFs), gradient tree boosting, extreme gradient boosting, linear regression, K-Nearest Neighbor, and Support Vector Machines (SVMs) are part of the non-NN-based model framework [28]. These models are discussed below, together with a brief survey of their usage.

- Random Forests (RFs)

This model has the advantage of low generalization error, rapid convergence, and minimal need for parameter adjustments. These features help prevent overfitting and make the model widely used in load prediction. The authors in [29] combine RF and DT techniques to increase the modeling performance. In [30], the authors employ the RF algorithm to categorize EVCSs into available and occupied states, attaining an accuracy of 94.8%. In [31], the performance of the RF model is compared to other ML-based EV demand-forecasting models. For scenarios with extremely complex and noisy data, RF models may overfit, reducing their performance. Additionally, the RF model is not interpretable, making it challenging to provide clarity for a proper understanding of the EV demand patterns.

- K-Nearest Neighbor (K-NN)

The K-NN algorithm generates substitute target variables that approximate the population distribution by estimating missing data based on the nearest observed values [32]. K-NN is utilized in [32] as a multivariate imputation model to improve the EVCS load forecasting. The evaluation result of K-NN models demonstrates superior forecasting accuracy under one of the evaluated high-missing-rate scenarios.

High-dimensional data might make it difficult for K-NN to accurately forecast EV charging demands. Furthermore, K-NN's dependence on distance measurements makes it sensitive to data size, requiring thorough preprocessing of data.

- Support Vector Machines (SVMs)

SVMs continuously predict values by finding the optimal hyperplane that maximizes the separation margin while minimizing the prediction errors [33]. To address nonlinearities, SVMs leverage kernel functions (the mathematical function used in ML algorithms) that perform an implicit transformation of the input data into a high-dimensional feature space [25]. In [33], the forecasted EV charging load is used as an input for the SVM model, and the projected EV charging load value was determined by accounting for many influencing factors, such as arrival time, state of charge, charging duration, charging power, and user behavior.

The choice of hyperparameters has a significant impact on SVM performance. SVMs may also have trouble identifying long-term relationships and intricate nonlinear patterns in time-series data.

- Ensemble Learning

Ensemble learning is an ML technique involving multiple models to effectively solve problems [30,34]. Most algorithms have limitations, and therefore the idea behind ensemble learning is that combining the predictions of multiple models enhances performance and improves accuracy [34]. The model also becomes more robust. The authors in [30] predict EV consumption using a stacked generalization. The prediction outcomes further indicate that employing stacking techniques, a form of ensemble learning, can effectively achieve reliable accuracy in predictive models for EV energy consumption.

Despite their excellent predictive potential, ensemble-learning approaches are computationally complicated, difficult to comprehend, and sensitive to data quality. Furthermore, their scalability and responsiveness to changing EV charging patterns are limited, especially in large-scale real-time forecasting conditions.

NN-Based Machine-Learning Forecasting

The NN-based ML forecasting models, i.e., Artificial Neural Networks (ANNs), comprise several architectures, such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Graph Neural Network (GNN) [35,36].

- Artificial Neural Network (ANN)

This prediction technique has been used in several studies [36–38]. The authors in [36], due to the discrete and asynchronous nature of charging events, developed a detailed data-handling method to generate meaningful time-series data. The input layer of an ANN model receives historical data on EV charging demand to predict the expected future charging demand of the electrical grid [38]. The ANN model has the disadvantage of handling time-series problems, like difficulty managing long-term dependency and capturing complex temporal patterns. Furthermore, ANN suffers from heavy dependence on manual feature extraction and labor-intensive parameter optimization [39].

1. Convolutional Neural Network (CNN)

CNNs consist of several key layers, including convolutional layers, rectified linear unit activation, pooling layers, and fully connected layers [35]. To address the complex and highly variable load patterns, the authors in [39] proposed a hybrid time-series forecasting model, specifically a CNN–Bidirectional LSTM approach, to forecast the EV charging demand and network voltage profile from the EV data without load flow performance. The results from the model show an accurate demand forecast that is better than the traditional CNN, and the network voltage profile was predicted. In another paper [40], the CNN and lion algorithm were combined to predict the short-term EVCS load. The results denote that the hybrid model offers accuracy and robustness. One of the advantages of CNNs is their ability to capture spatial and temporal patterns through convolutional operations. CNN algorithms, however, encounter challenges in forecasting time-series-related problems due to their reliance on fixed-length input sequence datasets [35].

2. Recurrent Neural Networks (RNNs)

Conventional network forecasting models are challenged with modeling problems containing sequential data because of limited memory [36,41]. In contrast, RNNs excel while working with sequential data alongside time-series data by integrating memory cells. By doing so, RNNs can effectively sustain and process information. Long Short-Term

Memory (LSTM), Gate Recurrent Unit (GRU), bidirectional RNN, and attention-based RNN are a few of the many types of developed RNNs that model sequential data [42]. RNNs are used for time-series datasets to predict the future of a dataset [43]. The authors in [36] apply an RNN model to forecast EV charging demand. In [42], the authors apply the LSTM model to forecast EV charging demand. Another special type of RNN is GRU [42]. It employs gating methods, considering an update gate and a reset gate to manage data-transfer efficiently between networks. Considering this, GRU is enabled to capture dependencies in sequential data and decrease the disappearing gradient problem [42]. In [35], the authors conducted a comparative study involving RNN, LSTM, and GRU. The results demonstrated that the GRU model outperformed the other models, indicating that GRU is better suited for EV demand forecasting than RNN and LSTM.

3. Graph Neural Network (GNN)

The GNN framework models information using nodes to represent entities and edges to characterize the relationships among them [44]. Hypothetically, in the context of EV charging demand, a node represents an individual Charging Station (CS) in the network of stations. Each node possesses specific data about the station. However, this transferred information is updated through aggregated layers, integrating features from all connected nodes and iteratively refining the node representation [44]. The authors in [45] predict the operational standing of charging stations using graphical convolutional networks (GCNs), accounting for the significant influence of surrounding traffic on the functionality of urban charging stations. Furthermore, in [46], the prediction of EV charging demand was accomplished using a developed algorithm, the Federated Meta-Learning Augmented Graph Convolutional Network (FMGCN). This algorithm was proposed to address the issue of frequent missing data when accessed through the Internet of Things (IoT) medium.

The GNN confronts scalability and computing efficiency issues, especially in complex networks. GNNs require careful design and optimization of the graph structure, which can be complicated and difficult to understand in various EV charging conditions.

4. Hybrid Approach

The hybrid approach combines two or more ML methods to leverage their strengths, accurately enhance predictions, and precisely manage the complex dynamic nature of EV demand [35,36]. This application is suitable for tackling forecasting problems that are nonlinear seasonal, and have random data patterns, due to its adaptive nature [3]. In [47], a hybrid model involving CNN-BiLSMT and Conv-BiLSTMA is proposed for time-series transductive learning. Similarly, in [48], the authors proposed a hybrid approach involving SARIMA–deep learning (DL) to predict EV charging demand. However, the drawbacks of the hybrid method are high computational complexity, difficulties in effectively fine-tuning the model and incorporating different algorithms, and difficulty interpreting the model [36].

Generative AI

This is another arm of AI that learns from fundamental patterns and existing data relationships to generate new datasets. Generative AI addresses the issue of data scarcity in real-world EV load demand problems by simulating many scenarios, considering EVCS location and user behavior. This technique accounts for irregularity and uncertainty in the charging patterns [49]. Generative Adversarial Networks (GANs), transformers, and Variational Auto-Encoders (VAEs) are some popular generative AI techniques used in EV charging-demand forecasting.

https://doi.org/10.3390/en19051131

- Transformer

This generative AI model processes input sequences with stacked encoders and decoders, each of which comprises a multi-head attention and a feed-forward neural network. The decoder likewise comprises masked multi-head attention, used to manage sequential dependencies [49]. In [50], the authors presented a transformer model for EV charging-demand forecasting. Additionally, in [45,46,51], the EV charging-demand forecasting was done by combining Graph Convolutional Networks (GCNs) and a transformer, forming GCNs–Transformer, to accurately and efficiently forecast Electric Vehicle Battery-Swapping Stations (EVBSSs). In [12,52], a forecast model for EV energy consumption and velocity was formed using transformer Markov Chain Monte Carlo (MCMC). Transformer models employ attention processes to determine the most significant time steps, allowing for very accurate long-term forecasting of EV charging demand.

- Generative Adversarial Networks (GANs)

The GAN algorithm has a generator and a discriminator [44]. The generator generates simulated EV demand data from arbitrary input, forming synthetic patterns that mirror genuine charging needs. Meanwhile, the discriminator evaluates the invented data, comparing it to the real EV charging-demand data [44]. From the inactive generated feedback provided by the discriminator, the fabricated data is refined, improving the accuracy of the data over time. The authors in [53] employed a modified GAN to assist the learning process, reducing the impact of the missing data on the system. In [54], from electric kickboard demand, synthetic time-series data was generated matching the original data distribution pattern using GANs. GAN is limited in capturing the stochastic nature of charging patterns. This drawback leads to inaccurate forecasted results [36].

- Variational Auto-Encoders (VAEs)

Similar to GANs, VAEs are capable of generating realistic data by learning from input data [35]. VAE structure comprises an encoder, decoder, latent space, and reconstructed input [55]. VAEs are useful for the generation and forecasting of EV charging data [55]. In [56], a deep-learning framework was employed to forecast renewable electricity demand. The model is combined with the VAE model to produce data samples and a Bi-LSTM to forecast the charging demand. Similarly, VAE is also used in [57] to build the load curve of the power grid load, recognizing the irregularities by measuring the error against the set threshold values.

VAEs offer robust probabilistic representation learning and uncertainty modeling, making them appropriate for complex and stochastic systems. However, their performance is limited by their capacity to capture acute and complicated data distributions.

Reinforcement Learning (RL)

Advancements in deep neural networks have made RL a highly impactful and versatile technique [58]. Unlike other machine-learning algorithms, RL focuses on maximizing cumulative rewards [59]. RL is an ML-based technique that makes sequential decisions by learning from interactions with its environment. However, RL finds it challenging to deal with complex problems that have high-dimensional state spaces. In [60], the authors used charging data from a Chinese energy service provider, including charging processes and station locations, to predict charging demand. They proposed a hybrid model combining a Temporal Encoder–Decoder LSTM (T-LSTM-Enc) with a Temporal LSTM incorporating time features (T-LSTM-Ori–Time Feature). The T-LSTM-Enc pre-trains the data to uncover hidden relationships, while the T-LSTM-Ori–Time Feature captures temporal features affecting charging-data-change variations. Additionally, in [61], the authors proposed multi-agent RL combined with LSTM to address grid load problems while minimizing cost.

In summary, non-learning-based methods like ARIMA, SARIMA, and Monte Carlo Simulation are simple to implement and good for handling uncertainties with limited datasets, but they struggle with nonlinearity and rely heavily on historical data. In contrast, network-based models such as RNN, LSTM, and GRU excel in capturing complex temporal patterns and adapting to nonlinear relationships. However, they require large datasets and significant computational resources. Ensemble learning and hybrid approaches enhance accuracy and robustness, while generative AI models address data scarcity and irregularities. Reinforcement learning enables dynamic optimization of charging demand and grid load balancing. However, these models require significant computational resources, are prone to overfitting, are less interpretable, are highly dependent on large amounts of high-quality data, and are complex to implement. NN-based models, such as LSTM and GRU, are effective for sequential data, while generative AI models like GANs and VAEs generate realistic synthetic data.

Although advanced learning-based models such as LSTM, GRU, GNN, Transformer, and hybrid architectures provide superior forecasting accuracy, their practical implementation is constrained by high computational requirements, large data dependency, scalability limitations, and reduced interpretability. Non-NN-based models (RF, SVM, and KNN) offer better deploy ability for medium-scale systems but may struggle with complex temporal dependencies. Generative AI and RL approaches are promising for uncertainty modeling and adaptive control; however, they require extensive training data and computational resources. This reveals a trade-off between predictive performance and real-world feasibility, highlighting the need for scalable and interpretable forecasting frameworks for EVCS planning.

To objectively evaluate forecasting accuracy and resilience, however, typical assessment criteria, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R^2), must be included. To further understand their effects on uncertainty propagation and planning optimization results, future studies should compare statistical and learning-based models in a methodical manner, utilizing unified datasets and uniform metrics.

Table 2 summarizes the commonly used quantitative performance metrics for evaluating both non-learning- and learning-based EV charging-forecasting models.

Table 2. Summary of quantitative metrics for non-learning- and learning-based EV charging forecasting.

Author/Year/Ref.	Quantitative Indices
Rashid et al. (2024) [1]	MAE, RMSE, MAPE
Akshay et al. (2024) [4]	RMSE, MAPE
Shahriar et al. (2021) [31]	RMSE, MAE
Zhu et al. (2019) [35]	MAE, RMSE, MAPE
El-Azab et al. (2023) [36]	RMSE, MAE
Koohfar et al. (2023) [50]	RMSE, MAPE, MAE

Non-learning-based techniques are often straightforward, transparent, and computationally inexpensive, thus making them appropriate for small-scale research and initial planning. Robust infrastructure design is supported by probabilistic techniques, which offer insightful information about risk and uncertainty. By incorporating nonlinear and temporal interactions, machine-learning and deep-learning models greatly improve forecasting accuracy; nevertheless, they come with a high computational cost and a big dataset need. By facilitating scenario creation and dynamic control, generative AI and reinforcement learning enhance predicting skills even further. As a result, hybrid and integrated frameworks that include probabilistic, statistical, and machine-learning techniques are showing promise as workable answers for realistic EVCS planning in the face of uncertainty.

2.2. Review of EVCS Planning

This section provides a concise overview of EVCS planning in the DN. The discussion in this section focuses on EVCS planning.The growing number of EVs adopted by users has been followed by the increasing deployment of EVCS in the DN. Moreover, CSs' deployment in DNs brings about several challenges, including technical, economic, and environmental impacts, among many others, affecting the DN operation [62]. Therefore, to overcome these mentioned challenges, EVCS planning is very important [62]. Planning EVCSs effectively involves many aspects, like technical impacts (power supply, active power loss, reactive power loss, voltage stability, and voltage deviation), economic impacts (investment cost, installation cost, operational cost, and maintenance cost), and environmental impacts (CO_2 emission) [63,64]. In this regard, this section discusses the various means applied to tackle planning-related problems. These include the planning algorithms, the techniques deployed to tackle the problems associated with the location and sizing of EVCSs, the objective functions, and the technical impacts of EVCSs on the distribution network.

Introducing EVs (transportation sector) into the power sector has reduced CO_2 emissions, thereby benefiting the environment [65]. However, the high inflow of EVs and the increasing number of CSs have introduced significant challenges, including power losses, voltage deviations, grid overloading, and power quality issues to the grid, and affect the utility service [24,66]. However, several solutions have been proposed to address these challenges, particularly focusing on the technical impacts of EV charging demand on generation capacity, transformer aging, and power quality [67]. It is important to address all of these challenges while managing EV charging infrastructures to enhance the system's reliability and stability [67].

Considering that EVCS are connected to the power grid, EV batteries are charged through the grid rather than the burning of fossil fuels [67]. Meanwhile, incorporating RESs into the EVCS-DN significantly reduces emissions, particularly in urban environments. The proper allocation of CSs in the grid reduces greenhouse gas emissions, as well as other pollutants, across both the power-generating plant and the transportation sector. Research has proven that EVCS allocation in the DN can lead to a reduction in CO_2, carbon monoxide, etc., producing lower emissions compared to ICE vehicles [68].

EVs offer both EV users and utilities financial benefits compared to ICE vehicles. EVs also lower fuel and operational costs. However, the initial investment cost of EVCSs is relatively high compared to the ICEVs, as well as the regular fueling stations [67]. In addition, slow EV adoption also reduces profits [69]. Nevertheless, with increase in EV production, along with CS expansion, associated EV and EVCS installation costs are expected to significantly decline [67].

2.2.1. Planning Algorithms

To address the challenges EVCS deployment poses to the DN, their allocation is optimally done. The planning algorithms are illustrated in Figure 3. In the Figure, the optimization algorithms are generally categorized into two types: deterministic and stochastic. Traditional (exact/deterministic) algorithms, such as linear programming (LP) [70], nonlinear programming (NLP) [71], and dynamic programming (DP) [72], have been used in solving optimization problems. These techniques are acknowledged for time efficiency and the ability to converge to local optima. On the other hand, they are challenged with difficulty escaping local solutions, risk of divergence, handling complex constraints, and challenges in computing first or second-order derivatives [73]. In addition, deterministic optimization techniques cannot solve network uncertainty problems introduced by intermittency [73]. Moreover, modern power systems have challenges, ranging from renewable energy uncertainties to load fluctuation that cannot be efficiently addressed using a deterministic optimization approach due to the complexity and the number of problems [74]. However, employing machine-learning theories in deterministic algorithm models can enhance the model's performance [74]. Stochastic techniques, particularly the metaheuristic algorithms, have less chance of encountering the abovementioned disadvantages of deterministic algorithms while addressing optimization issues. Metaheuristic algorithm applications are based on an empirical theoretical basis, inspired by living things' behavior. These algorithms can be adjusted to fit the underlying power system problem [74]. Finally, metaheuristic algorithms are the superior choice for optimization problems in power systems due to their robustness, flexibility, and ability to address system uncertainties, which are critical in achieving efficient solutions in complex, modern networks. Figure 3 describes the classification of various optimization algorithms used in the power system. Table 3 provides a summary of the most popular algorithms used for planning EVCS in DN. The Table presents the advantages and disadvantages of the listed algorithms.

Table 3. Summary of EVCS planning algorithms.

Algorithms/Ref.	Advantage	Disadvantage
Mixed-integer linear program (MILP) [75–77]	MILP models a wide range of optimization problems, including EVCS allocation. It easily handles complex problems and obtains feasible solutions. It applies to multi-objective planning problems.	MILP models are often complex and time-consuming, requiring detailed datasets. Their ability to achieve a globally optimal solution is highly sensitive to problem formulation.
Alternating direction method of multipliers (ADMM) [78,79]	ADMM is effective for decomposing problems into sub-sections, handling complex constraints, and ensuring convergence to global optimum in convex optimization problems. It is suitable for tough problems and those with limited datasets, improving solution efficiency even for large and complex issues.	ADMM struggles with non-convex problems, as convergence is not guaranteed. It catches challenges in solving large problems, requiring advanced techniques. It converges slowly for high accuracy, but it can be memory-intensive depending on the nature of the decomposed problems.
Sequential quadratic programming (SQP) [80,81]	SQP is computationally efficient for smaller problems and is suitable for solving problems with nonlinear equality and inequality constraints. SQP performs well with problems that have continuously differentiable objective functions and constraints.	SQP converges to a local optimum instead of a global optimum if the initial starting point is poorly selected. It struggles with non-continuously differentiable functions, affecting its accuracy and convergence. Its implementation is complex.
Dynamic programming (DP) iteration [82–84]	DP is efficient for complex tasks due to less computation time. It provides planners with flexible solutions by adjusting to varying charging conditions, like energy prices and demand. DP addresses multi-objectives like minimizing cost and maximizing reliability by including weighted objectives in its structure.	DP is too resource-intensive for large-scale problems due to its recursive calculations and high memory demand. As the number of decision variables grows, DP's complexity increases exponentially, making multi-parameter optimization planning problems more challenging to solve.
Snake optimization algorithm (SOA) [85,86]	SOA strikes a balance between global and local search, preventing premature convergence. It is versatile, applicable to a wide range of optimization problems, and easy to implement.	SOA struggles with complex problems and may need hybrid algorithms to achieve global optimal solutions. It converges to a local optimum under certain conditions, acquiring the wrong solution.

Table 3. *Cont.*

Algorithms/Ref.	Advantage	Disadvantage
Particle swarm optimization (PSO) [87–89]	PSO has fewer parameters, making it easier to implement. Its performance requires only a few control parameters. PSO's social component enables it to explore the global search space, reducing the chance of trapping in local optima.	PSO may prematurely converge to a local optimum, and its performance tends to decline with complex problems. It often requires hybridization with other algorithms to effectively handle more complex issues.
Genetic algorithm (GA) [90–92]	GA excels in exploring complex searches, preventing them from being trapped in a local optimum. It addresses diverse optimization challenges, especially nonlinear problems. It tackles combined optimization tasks like routing. GA can be modified.	GA struggles to compute large and complex problems for its numerous solutions. It cannot always find global optimum solutions for these problems, and its performance depends on parameters like population size, mutation rate, crossover rate, and selection strategy.
Grey wolf optimization (GWO) [93,94]	GWO parameters are few, making its implementation easy. It balances global search and local search, guided by its leadership structure. GWO avoids local optima while searching for global optima and outperforms in multi-modal scenarios with many local optima.	GWO struggles with premature convergence in complex and large-scale problems. It declines in performance for high-dimensional issues. It has fewer control parameters, and its performance is highly sensitive to them.
Teaching–learning-based optimization (TLBO) method [95–97]	TLBO avoids algorithm-specific parameters, requiring only population size and iteration, thus reducing its computational complexity and increasing efficiency. It does not require additional parameters to balance exploration and exploitation and escapes local minima, enhancing its global optimum search with a group learning-based approach.	When population growth halts, TLBO experiences stagnation. Its performance is not always superior in specific problem cases. Rapid learning from teachers and peers can quickly reduce population diversity, limiting exploration and potentially missing good solutions. TLBO's performance is dependent on population size.
Ant colony optimization (ACO) [98,99]	ACO is suitable for discrete optimization problems and is flexible for complex, multi-objective scenarios. It is self-adaptive, enhancing solution accuracy over time by adjusting iterations based on previous results. ACO is also ideal for optimization problems with parameters that vary over time.	ACO has a high computational cost, particularly with many iterations. It is sensitive to initial conditions and parameter settings (e.g., pheromone decay rate and evaporation rate). Additionally, ACO implementation is complex and requires careful parameter tuning.

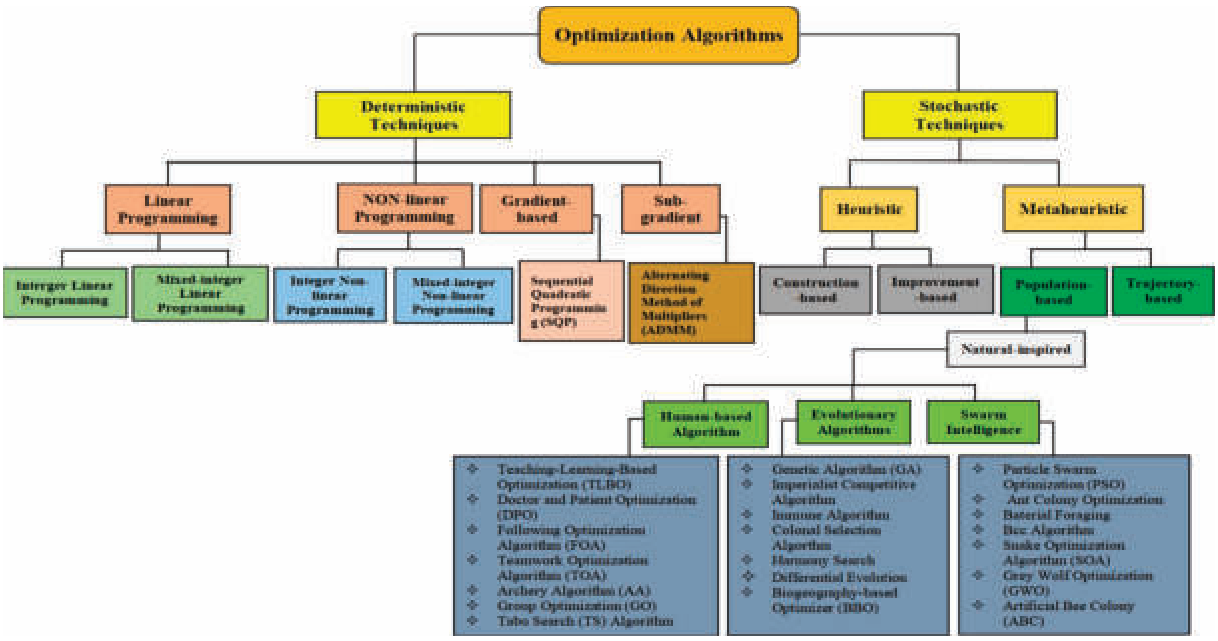

Figure 3. Classification of optimization algorithms.

2.2.2. Objective Function

Table 4 summarizes several articles that implemented EVCS planning using several algorithms prioritizing technical, economic, and environmental impacts as objective functions.

A review of EVCS planning objectives, which is included in Table 4, finds a strong emphasis on technical and economic factors, with voltage stability, power loss, and installation cost being the most addressed elements. While many studies focus on performance improvement and cost reduction, environmental factors like emissions and CO_2 reduction are less typically examined. Furthermore, the inclusion of reliability evaluation is significantly limited, with just a tiny percentage of the examined publications addressing this crucial element. This suggests that, despite extensive coverage of technical and economic objectives, the integration of environmental sustainability and reliability is inadequate. Future studies should use a more holistic approach, incorporating reliability factors, as well as environmental and financial factors, in order to create resilient, efficient, and sustainable EV charging infrastructure.

Table 4. Summary of EVCS planning algorithms (method).

Ref. No.	Author	Objective Function										
		Technical Criteria					Economy Criteria				Envir. Criteria	Reliability Criteria
		Q_{loss}	P_{loss}	V_{Devi}	P_{sup}	VSI	Inst Cost	Invst Cost	OP. Cost	Mnt. Cost	Ems CO_2	
[100]	Hammam et al. (2024)							✓	✓	✓		
[101]	Abdelaziz et al. (2024)		✓	✓			✓	✓				✓
[63]	Bilal et al. (2022)		✓		✓	✓	✓	✓	✓	✓	✓	
[102]	Kumar et al. (2024)	✓	✓	✓		✓						✓
[103]	Prakobkaew et al. (2024)		✓				✓					
[104]	Eid El-Iali et al. (2024)							✓	✓		✓	
[105]	Balu, Mukherjee (2024)	✓	✓	✓					✓		✓	✓
[106]	Hu, Li et al. (2024)						✓		✓		✓	
[107]	Bilal et al. (2021)		✓	✓		✓						✓
[108]	Keramati et al. (2024)		✓				✓	✓	✓			
[86]	Nafeh et al. (2024)						✓	✓	✓	✓		
[109]	Balu et al. (2023)		✓	✓					✓			
[110]	Krishnamurthy et al. (2023)		✓	✓		✓	✓		✓			
[111]	Jin et al. (2024)			✓		✓	✓	✓	✓	✓		
[112]	Rene et al. (2023)	✓	✓	✓								
[113]	Archana et al. (2021)		✓			✓						✓
[114]	Chen, et al. (2021)	✓	✓	✓			✓					
[115]	Bilal et al. (2021)	✓	✓	✓								

3. EV and RES Integration in the Distribution Network

Addressing the growing electricity demand is a major challenge for utilities worldwide [116]. Currently, 75% of global energy needs are met by combusting fossil fuels, resulting in significant CO_2 emissions, global warming, depletion of fossil fuel reserves, and rising fuel prices. This situation necessitates a shift towards renewable energy resources [116]. Against this backdrop, adopting RES in the power grid is increasing and becoming the preferred RES technology. RES integration aims to reduce carbon emissions [116]. According to [117,118], renewable energy distributed generation units are viable alternatives to conventional power plants, significantly contributing to the rising load demand. The authors further recognize that the total installed capacity from RESs increased from approximately 3100 GW in 2022 to 3360 GW in 2023, marking an 8.4% increase within a year. By the end of 2024, similarly, Ref. [118] acknowledged a rapid global growth in RES capacity to 4448 GW, representing a 15.1% increase in renewable energy capacity during the 2023 period and amounting to 585 GW.

Despite the benefit of RES integration into the grid, it poses intermittent uncertainty, complicating its integration into electric power systems [116]. When RESs are incorporated into the power grid, the variable power generation leads to frequency fluctuations, destabilizing the power system and resulting in power quality and fluctuation in power output [119]. To mitigate these challenges, some authors propose the integration of ESSs or the employment of controlled dispatch loads to assist in managing these fluctuations by storing excess energy or supplying it during insufficiency [120]. Additionally, the authors in [121,122] propose ESSs comprising multiple EV batteries as a key component to be integrated along with RESs in the distribution network.

However, the integration of EVs and RESs into the grid presents several challenges due to their widespread adoption. For instance, in [123], the authors mentioned the irregularities of PV and wind, and the introduction of EVs to the grid will make both demand and supply more intermittent, resulting in energy losses in the distribution system [124]. Consequently, sizing and placing DGs, as well as EV charging infrastructure, present intricate challenges due to various conflicting constraints and objectives. Thus, optimization techniques are employed to address these issues [125]. Table 5 provides a comprehensive summary of studies that considered the optimal location and sizing of EVCS and RES integration in the power grid. The objective function in each study is underscored as technical, economic, or environmental.

Optimal siting and sizing of EVCSs and RESs in distribution networks are commonly evaluated using multi-dimensional quantitative metrics. Technical indicators include active and reactive power loss reduction (kW/kVAR), voltage deviation (p.u.), and voltage stability index (VSI). Economic metrics comprise capital investment cost, operational cost, life-cycle cost, and net present value (NPV). Environmental performance is assessed through CO_2 emission reduction (kg or %), while reliability is evaluated using indices such as System Average Interruption Frequency Index (SAIFI), System Average Interruption Duration Index (SAIDI), and Energy Not Supplied (ENS). Multi-objective formulations typically balance these metrics to achieve techno-economic–environmental optimality.

To reduce the computational burden associated with optimal location and sizing problems, several acceleration strategies have been reported in the literature. Sensitivity-based screening methods can pre-identify candidate buses, thereby reducing the dimensionality of the search space. Additionally, metaheuristic optimization algorithms such as PSO and GA provide optimal solutions with faster convergence compared to exhaustive search approaches. Scenario reduction techniques and surrogate-assisted optimization further improve computational efficiency under uncertainty. These strategies offer practical shortcuts for planners while maintaining acceptable optimality levels.

Table 5. Summary of research surrounding optimal location and sizing of EVCS and RES integration in the distribution network.

Author/Year /Ref.	Proposed Strategy	RES Type	Objective Function									
			Tech. Criteria				Eco. Criteria				Env. Criteria	Rel. Criteria
			Q_{loss}	P_{loss}	V_{Devi}	VSI	Inst Cost	Invst Cost	OP. Cost	Mnt. Cost	Ems CO_2	
Bilal et al. (2022) [63]	Modified Salp Swarm Algorithm	Solar (PV)		Y		Y	Y	Y	Y	Y	Y	
Ul Hassan et al. (2023) [64]	Teaching–learning-based optimization	Solar (PV)		Y		Y	Y	Y	Y	Y	Y	
Eid et al. (2024) [126]	Honey badger algorithm (HBA)	Wind Turbine		Y								
Adetunji et al. (2022) [127]	Whale optimization algorithm–genetic algorithm (WOAGA)	Solar (PV)		Y	Y	Y	Y		Y		Y	
Vijayan et al. (2023) [128]	Knuth's Algorithm S	Solar (PV)		Y	Y	Y						
Eid et al. (2022) [129]	Gorilla Troop Optimizer (GTO) algorithm	Solar (PV) and WT		Y	Y	Y						
Bilal et al. (2021) [107]	Hybrid of grey wolf optimization and particle swarm optimization (HGWOPSO)	Solar (PV)		Y	Y		Y					Y
Ponnam et al. (2020) [130]	Harries Hawks Optimization (HHO) Algorithm	PV, WT		Y	Y	Y	Y					
Fokui et al. (2021) [131]	Bacterial foraging optimization algorithm–particle swarm optimization (BFOA-PSO) algorithm	Solar (PV) systems	Y	Y	Y							
Zeb et al. (2020) [132]	Particle swarm optimization (PSO)	Solar (PV)		Y	Y		Y					
Zhang et al. (2021) [133]	Multi-objective natural aggregation algorithm (MONAA)	Wind power		Y				Y				
Pompern et al. (2023) [134]	Particle swarm optimization (PSO)	Solar (PV)	Y	Y	Y		Y		Y	Y		

Table 5 shows that the majority of previous research on EVCS and RES integration has prioritized technical and financial objectives such as decreasing active/reactive power losses, voltage variation, and investment/operational expenses. Advanced metaheuristic optimization techniques such as PSO, HBA, GWO, and hybrid algorithms have been widely used to increase solution efficiency and resilience. Few studies have included environmental factors like CO_2 emissions and long-term reliability. This identifies a research gap in which future work should focus on comprehensive multi-objective formulations that balance technical, economic, environmental, and reliability factors.

The findings of the statistical analysis of Table 5 show the following: (a) The most commonly considered objectives are technical criteria, which appear in over 99% of the examined studies and include active and reactive power loss, voltage deviation, and voltage stability index. ((b) About 70% of the objectives take into account economic factors, such as installation, investment, operating, and maintenance costs. Only 35 percent of the research addresses environmental criteria, including the reduction of CO_2 emissions. Just 18% of the examined publications address reliability requirements, making them the least addressed. This statistical realization draws attention to an imbalance in research, where dependability and environmental factors are understudied while technological optimization takes center stage. In order to enhance the comparative evaluation and clearly indicate research gaps, the quantified analysis is now included in the revised manuscript.

Table 6 outlines load modeling methods, PV characteristics, EVCS charging profiles, charger levels, power ratings, and integration with BESS. This allows for comparisons of how different research represents actual distribution systems, pricing infrastructures, and renewable penetration levels.

Table 6. Summary of research surrounding with parameters related to EVCS and RES integration in the distribution network.

Author/Year/Ref.	Load Parameters	PV Characteristics	EVCS Charging Profile
Adetunji et al. (2022) [127]	➢ Balanced load (residential, commercial, and industrial)	➢ Rated capacity (4.22 MW)	➢ Slow charger (11 kW power rating)
Vijayan et al. (2023) [128]	➢ Unbalanced load	➢ Uncertain solar PV units with rated capacity	➢ Slow EV Charging Station (3.3 kW) and fast-charging station (50 kW)
Eid et al. (2022) [129]	➢ Residential balanced load	➢ Solar PV Units with Rated Capacity	➢ Level 1 (up to 1.8 kW and 120 V single-phase) and Level 2 (up to 19.2 kW and 220 V single-phase) EV charger
Bilal et al. (2021) [107]	➢ Residential balanced load	➢ Solar PV unit with rated capacity of 1.244 MW.	➢ Fast EVCSs with a charger rating of 50 kW
Ponnam et al. (2020) [130]	➢ Residential balanced load	➢ Solar PV unit with rated capacity of 2873.12 kW	➢ Level 2 AC/DC (7–22 kW per charger) EV charger
Fokui et al. (2021) [131]	➢ Balanced load (residential and commercial)	➢ Total PV capacity of 2274.72 kW	➢ Level 1 (11 kW) and Level 2 (22 kW) EV chargers
Zeb et al. (2020) [132]	➢ Unbalanced load (residential and commercial)	➢ Solar PV unit with capacity of 1200 kW	➢ Level 1 (1.9 kW), Level 2 (4 kW) and Level 3 (Up to 100 kW) EV chargers

Table 7 summarizes planning horizons (short-term, 24 h, and long-term) and practical operational constraints (power balance, voltage limits, thermal limits, SOC limits, charger capacity limits, etc.), thereby highlighting real-world operational challenges considered in the literature.

Table 7. Summary of research surrounding constraints related to EVCS and RES integration into the distribution network.

Author/Year/Ref.	Practical Constraints
Adetunji et al. (2022) [127]	Power balance, nodal voltage, BESS operation, and EV load constraint
Vijayan et al. (2023) [128]	Voltage unbalance factor limits, extreme tap position limits, voltage regulation limits, power balance, nodal voltage, and line current limits
Eid et al. (2022) [129]	State-of-Charge limits, Size of BES Limits, PV and wind turbine limits, power balance, and nodal voltage limits
Bilal et al. (2021) [107]	DG limits, power balance, and nodal voltage limits
Ponnam et al. (2020) [130]	Number of Charging points and Charging capacity limits, power balance, active power, reactive power, and nodal voltage limits
Fokui et al. (2021) [131]	Charging Power of EVCS limits, power balance, and nodal voltage limits
Zeb et al. (2020) [132]	Thermal limits, Charging capacity of EVCS limits, charger number limits, parking slots limits, state of charge, and nodal voltage limits
Pompern et al. (2023) [134]	Power and capacity of BESS limits, power balance, and nodal voltage limits

3.1. Frameworks, Regulatory Challenges, and Socioeconomic Barriers in EVCS–RES Integration

Socioeconomic constraints, legal frameworks, and policy frameworks all have a significant impact on how EVCSs and RESs are widely integrated. Although technical innovations facilitate effective planning and operation, their practical implementation is heavily reliant on favorable regulatory frameworks, electrical market configurations, carbon pricing plans, and customer acceptability. According to recent research, EVCS planning results are greatly impacted by regulatory policies, including demand-response programs, dynamic energy pricing, Vehicle-to-Grid (V2G) market participation, and carbon trading systems.

The thorough analysis of [23], in particular, emphasizes the interplay between the carbon and electricity markets, showing how well-coordinated market mechanisms may encourage the use of EVs, improve the use of RES, and lower emissions across the board. Their results highlight the significance of market structure, bidding tactics, and regulatory cooperation in facilitating both economically and ecologically sustainable EV integration.

3.1.1. Challenges in EVCS-RES Planning

Large-scale adoption of EVs is hampered by a number of issues, including expensive upfront vehicle and battery prices, range anxiety, lengthy charging periods, and inadequate charging infrastructure. As intermediaries for EV users and grid operators, aggregators face difficulties in managing highly variable and unpredictable demand, coordinating unregulated charging patterns, and offering dependable flexibility services to Distribution System Operators (DSOs) and Transmission System Operators (TSOs) while preserving market efficiency and grid stability. In the meantime, aging infrastructure, the growing use of decentralized RES, and the rapidly rising demand for EV charging present challenges for DSOs. These factors collectively place severe thermal, voltage, and capacity constraints on current networks, requiring expensive grid reinforcement, sophisticated asset management, and intelligent digital solutions to ensure consistent and efficient power delivery.

3.1.2. Policies and Incentives

With extensive regulatory frameworks, financial incentives, and infrastructure investments currently encompassing the majority of global vehicle markets, global regulations and incentives have been instrumental in speeding up the adoption of EVs and the deployment of charging infrastructure. Mandates for zero-emission vehicles, fuel economy requirements, purchasing subsidies, tax benefits, and significant expenditures in charging infrastructure are important tactics, especially in major regions like the United States, the European Union, China, and Norway [135]. Through technological breakthroughs and economies of scale, these measures have substantially increased EV sales, improved the density of charging networks, and decreased battery prices, making EVs more affordable than conventional vehicles.

By assisting manufacturers, customers, and infrastructure development, government initiatives like Faster Adoption and Manufacturing of Hybrid and Electric Vehicles (FAME) and the government Electric Mobility Mission Plan have bolstered EV adoption in India. Two- and four-wheeler categories have seen the greatest increase. Notwithstanding significant advancements, obstacles still exist in the form of expensive initial costs, inadequate charging infrastructure in some areas, legal restrictions, and administrative hold-ups, all of which contribute to a delayed adoption [135]. However, it is anticipated that further policy improvement, public–private collaborations, and focused incentives will improve EV market growth and infrastructure preparedness even more, assisting the worldwide shift to low-carbon and sustainable transportation systems.

https://doi.org/10.3390/en19051131

Socioeconomic issues also continue to be significant obstacles to the general adoption of EVCS-RES, including high investment costs, accessibility of charging infrastructure, tariff uncertainty, user behavior, equality concerns, and regional policy discrepancies. These difficulties reflect the need for integrated planning frameworks that consider societal acceptance, economic incentives, technological viability, and regulatory compliance. Therefore, in addition to conventional technological goals, future EVCS planning approaches should consider market involvement models, regulatory restrictions, and socioeconomic success metrics.

4. Discussion and Conclusions

This review discusses the integration of EVCSs and RESs into distribution networks. This shift is driven by global sustainability goals and decarbonization efforts, presenting both challenges and opportunities. Here are the key findings gathered from the survey.

- Optimal planning and placement of EVCSs and RESs can significantly enhance power quality, minimize energy losses, reduce infrastructure costs, and lower CO_2 emissions. Strategically placing RESs near EVCSs reduces grid dependence and alleviates grid stress during peak load hours.
- Most of the work has modeled EV load demand and PV generation in a simplistic and deterministic manner, whereas both should be treated stochastically by considering factors such as EV arrival/departure times, battery degradation, solar irradiance variability, temperature fluctuations, and weather uncertainties. Also, for efficient planning, advanced forecasting methods for EV, wind, and solar demand are necessary.
- Various algorithms have been proposed for the optimal planning of integrated EVCS and RES systems, ranging from deterministic to advanced stochastic approaches. However, metaheuristic algorithms are ideal for power system optimization problems due to their robustness, flexibility, and effectiveness in handling system uncertainties, which are crucial for efficient solutions in modern networks. Recently, hybrid optimization methods such as BFOA-PSO and WOAGA have demonstrated superior performance by combining the strengths of individual algorithms to achieve faster convergence, improved accuracy, and better exploration–exploitation balance, making them suitable for dealing with the complexity of EVCS-RES integration.
- Most existing studies on EVCS and RES integration have concentrated on technical issues such as power losses, voltage stability, and economic benefits. However, limited attention has been given to environmental impacts and long-term reliability. Moreover, comprehensive investigations that integrate technical, economic, environmental, and reliability impacts with the application of advanced forecasting techniques and optimization algorithms are still lacking.
- A key insight from the survey is that while numerous studies have proposed advanced deterministic and metaheuristic algorithms for optimal placement and sizing, fewer works address uncertainty propagation, coordinated energy management, and long-term reliability in an integrated manner. Optimization robustness should therefore not be evaluated solely by convergence speed or objective value improvement, but by resilience against renewable variability, EV demand fluctuations, and planning horizon uncertainties.
- The growing penetration of RESs and large-scale EV charging highlights the strategic role of battery energy storage systems (BESSs) as an enabling technology. Coordinated active–reactive power control and intelligent storage dispatch can mitigate voltage deviations, reduce losses, and enhance reliability under stochastic conditions. However, such operational coordination is still insufficiently embedded within many planning models.

From these findings, there is a need for future interdisciplinary collaboration among power system engineers, data scientists, economists, and policymakers to further improve this technological area. Here are a few future research issues to be prioritized:

- ➢ The fluctuation of renewable energy and EV charging demand creates substantial issues for grid operators. Traditional statistical and probabilistic forecasting approaches are extensively employed, but they frequently fail to capture the nonlinear and stochastic character of these uncertainties. Future research should concentrate on AI-based forecasting systems that can better predict complex patterns, enhance accuracy, and strengthen grid planning and operation.
- ➢ Conventional optimization techniques frequently have drawbacks, such as premature convergence to local optima and difficulty managing the nonlinear, dynamic nature of integrated energy systems. These flaws diminish their efficacy in balancing several, often conflicting, objectives under uncertainty. To address these difficulties, more advanced optimization approaches with multi-objective and methodologies are necessary, resulting in robust and globally optimum solutions.
- ➢ The majority of the recent research on EVCS and RES integration have generally concentrated on technical elements like power losses, voltage stability, and economic advantages, with little emphasis on the environmental impacts and long-term reliability evaluation of the distribution network. However, as EVCSs and RESs become more widely used, reliability becomes an increasingly important aspect in ensuring the long-term viability of grid operations. Future studies should explore the long-term impacts on infrastructure and planning, with a comprehensive focus on technical, economic, environmental, and reliability aspects.
- ➢ The present research on EVCS and RES integration focuses on both technical and economic optimization, with very little attention paid to commercial models and policy frameworks. Large-scale adoption may confront obstacles in terms of investment risks, participation of stakeholders, and customer acceptability in the absence of proper governmental support and new commercial strategies. Future research should thus focus on researching sustainable business models and policy mechanisms that may motivate stakeholders and ensure the optimal integration of EVCSs and renewable energy.
- ➢ Future studies should develop integrated optimization frameworks that jointly determine EVCS placement and BESS sizing, scheduling, and active–reactive power support. Such models should evaluate system robustness under uncertainty and quantify the reliability and voltage regulation benefits of coordinated storage control in RES-dominated distribution networks.
- ➢ The majority of the current research uses static or one-period optimization models. Multi-stage stochastic planning frameworks that concurrently take into account scenario-based RES generation uncertainty, probabilistic EV arrival/departure behavior, and load growth forecasts over medium- and long-term horizons should be developed in future studies. Planners would be able to explicitly quantify uncertainty propagation and system risk exposure by using optimization approaches that are either chance-constrained or distributionally resilient.
- ➢ Operational control and siting decisions are frequently separated in current studies. Future models have to incorporate network reconfiguration, coordinated active–reactive power regulation, BESS size and dispatch, and EVCS deployment. An efficient methodological framework for integrating operational and investment choices might be offered by bi-level or hierarchical optimization frameworks.

- It is obvious that reliability indices (such SAIDI, SAIFI, and ENS) must be explicitly included in optimization formulations. Future studies should create objective functions that take reliability into account, including failure rate modeling and component aging, and use scenario-based stress testing to examine resilience in the extreme events.
- To facilitate quantitative trade-off analysis between cost, reliability, and environmental performance, future research should incorporate life-cycle emission metrics, model marginal emission factors, and directly integrate carbon pricing or emission constraints into multi-objective formulations instead of qualitatively discussing sustainability.
- Future research should employ ensemble learning or deep learning for EV and RES demand prediction, incorporate probabilistic forecasting outputs into optimization models, and quantify forecast error effect using sensitivity or scenario analysis rather than utilizing forecasting as a preprocessing step.
- Future research should go beyond technological optimization and directly include regulatory compliance limitations, incentive mechanisms, and market design factors into multi-objective EVCS–RES planning models. Scenario-based assessment of carbon taxation levels, subsidy schemes, and reliability requirements can lower deployment hurdles, including investment risk, stakeholder reluctance, and infrastructure finance challenges, while offering policymakers evidence-based recommendations.

In conclusion, incorporating EVCSs and RESs into the distribution power system presents significant challenges but offers substantial opportunities for creating more sustainable and efficient energy systems. Continued research, innovation, and collaboration among stakeholders are crucial to overcoming barriers and realizing the full potential of that integration in modern power systems.

Author Contributions: Conceptualization, S.T., E.B.F. and S.R.G.; methodology, E.B.F. and S.R.G.; software, E.B.F., S.R.G. and S.T.; validation, E.B.F., S.R.G., S.T., F.L. and P.A.; formal analysis, S.T., E.B.F. and S.R.G.; investigation, S.T., E.B.F., S.R.G. and F.L.; resources, S.R.G., S.T. and F.L.; data curation, S.T. and E.B.F.; writing—original draft preparation, S.T. and E.B.F.; writing—review and editing, S.R.G., P.A. and F.L.; visualization, E.B.F. and S.R.G.; supervision, S.R.G., P.A. and F.L.; project administration, S.R.G., P.A. and F.L.; funding acquisition, S.R.G. and F.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analyzed in this study.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this paper:

LSE	load serving entity	PV	Photovoltaic
E	energy	Q_{loss}	Reactive power loss
O.P	operational	P_{loss}	Active power loss
Ems	emission	V_{Devi}	Voltage deviation
Invst/Syst	investment/system	Inst	Installation
Rev	revenue	CO_2	Carbon
Rel/Stab	reliability/stability	kWh	kilowatt hour
Mnt.	maintenance	Ref.	Reference
WT	wind turbine	Env.	environmental
Tech.	technical	P_{sup}	supply power
Eco.	economic	VSI	Voltage Stability Index

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